EFFICIENT ECG COMPRESSION BASED ON *M*–CHANNEL MAXIMALLY DECIMATED FILTER BANKS

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ABSTRACT

A filter bank–based algorithm for ECG compression is developed in this paper. The proposed method utilises a nearly-perfect reconstruction cosine modulated filter bank to split the incoming signals into several subband signals that are then quantised through thresholding and Huffman encoded. The advantage of the proposed method is that the threshold is chosen so that the quality of the retrieved signal is guaranteed. In this paper it is shown that the compression ratio achieved is an improvement over those obtained by previously reported thresholding-based algorithms.

Keywords: ECG compression, filter banks, subband coding.

1. INTRODUCTION

Several wavelet-based ECG compression methods have recently been developed that report good performance [1]–[3]. Among the reported algorithms, those based on wavelet coefficient thresholding have shown to be efficient and yield high compression ratios (CRs) [3]. In this work, we present an easy to use and efficient ECG compression scheme based on a *M*-channel maximally decimated filter bank with a parallel structure that guarantees the quality of the retrieved signal. In [4, 5] are shown previous works of ECG subband coding.

The proposed method, which is based on that originally reported in [6] incorporates several innovations, including the quantisation of the subband signal samples with less resolution than the original signal samples and entropy-coding by means of a Huffman coder. As a result, the algorithm performs significantly better than other approaches developed using similar techniques.

Tests are carried out using the MIT-BIH Arrhythmia Database and the Percentage Root-mean-square Difference (PRD) measurement criteria to evaluate the quality of the retrieved signal. Accordingly, let $x[n]$ and $\hat{x}[n]$ be the original and the reconstructed signals. The PRD is then defined as:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N} \left(x[n] - \hat{x}[n]\right)^2}{\sum_{n=1}^{N} \left(x[n]\right)^2}} \times 100 \ , \tag{1}$$

As the PRD is heavily dependent on the mean value, it is more appropriate to use the modified criteria:

$$PRD1 = \sqrt{\frac{\sum_{n=1}^{N} \left(x[n] - \hat{x}[n]\right)^2}{\sum_{n=1}^{N} \left(x[n] - \bar{x}[n]\right)^2}} \times 100 \ , \tag{2}$$

where $\bar{x}[n]$ is the mean value of the signal. Furthermore, it is established in [7], that if the PRD1 value is between 0 % and 9 %, the quality of the reconstructed signal is either "very good" or "good", whereas if the value is greater than 9 %, its quality group can not be determined. As we are strictly interested in very good and good reconstructions, it is taken that the PDR value, as measured with Eq. 2, must be less than 9 %.

The PRD parameter is a global criterion that does not take into account local effects. Nevertheless, in medical diagnosis based on signals, local behaviour is very significant. Therefore, it worth to complement with other parameters that could give an idea about those local effects. In this work, visual study of error signal has been considered to show the behaviour regarding local effects. Error signal $e[n]$ is calculated as the difference between original and reconstructed signals:

$$e[n] = x[n] - \hat{x}[n], \tag{3}$$

The outline of the paper is as follows. In Section 2, every stage of the compressor is explained and in Section 3 we present the performance of the compressor. Finally, in Section 4 our conclusions are presented.

2. COMPRESSION SCHEME

The proposed algorithm continuously processes the incoming ECG by operating on non–overlapped blocks of N samples. Thus no QRS detection or heartbeat segmentation is performed. The overall block diagram of the algorithm consists of three stages:

Stage 1 Decomposition of every input block with a Nearly–Perfect Reconstruction Cosine Modulated Filter Bank (N–PR CMFB): the incoming signal is split in the frequency domain giving several subband signals so that the original information is not equally distributed among them.

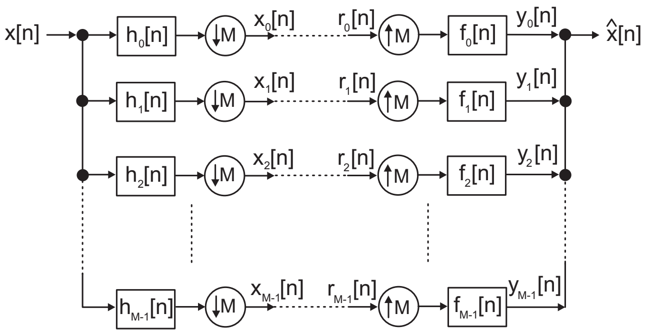

Figure 1: M-channel maximally decimated filter bank.

Stage 2 Thresholding of the subband signals in a fashion that guarantees the quality of the retrieved signal. The purpose is to chose the samples that contributes most significantly to the original waveform rejecting the others. Thus this stage leads to an information lost.

Stage 3 Huffman coding of the quantised subband signals.

2.1 Nearly–perfect reconstruction cosine modulated filter banks

A N–PR CMFB is a subclass of modulated M-channel maximally decimated filter bank whose structure is as shown in Fig. 1. All the analysis $h_k[n]$ and synthesis filters $f_k[n]$, $0 \leqslant n \leqslant L$, $0 \leqslant k \leqslant M-1$, can be obtained through the modulation of a low–pass prototype filter $p[n]$ as follows:

$$h_k[n] = 2 \cdot p[n] \cdot \cos\left((2k+1)\frac{}{2M}\left(n-\frac{L}{2}\right)+(-1)^k\frac{}{4}\right),$$
$$f_k[n] = 2 \cdot p[n] \cdot \cos\left((2k+1)\frac{}{2M}\left(n-\frac{L}{2}\right)-(-1)^k\frac{}{4}\right). \quad (4)$$

These systems offer almost, but not true, perfect reconstruction (PR). In the proposed method, a 191–order 16–channel N–PR CMFB is utilised based on good results reported from previous work [6]. The prototype filter is designed utilising the prototype filter design technique proposed in [8]. The problem can be stated in several different ways, but the purpose consists in minimizing

$$ = \left|\left|P\left(e^{j /2M}\right)\right| - 1\big/\sqrt{2}\right|, \quad (5)$$

where $P\left(e^{j}\right)$ is the frequency response of the prototype filter. When we use an appropiate FIR filter design technique (by windowing or by means of the Parks–McClellan algorithm), we can guarantee that the frequency response of the prototype filter approximately satisfies the power complementary property. In other words, this technique controls the position of the 3 dB cuttoff frequency of the prototype filter and sets it approximately at $/2M$. In this way it is possible to reduce the amplitude distortion and the aliasing errors introduced in the filter. Particularly in this work, a Blackman window has been used to design the prototype filter by windowing.

On the other hand, the use of N–PR CMFB takes advantage of the fact that it can be efficiently implemented by means of polyphase structures that minimize the computational cost. In [6] we present the study of the computational complexity for the proposed N-PR CMFB.

2.2 Quantisation algorithm

Once the ECG signal is decomposed, the subband signals are thresholded. To control the quality of the reconstruction, a target PRD (PRD_{target}) is established *a priori*. Thus, the applied thresholding is dependent on PRD_{target}. To describe the approach utilised to achieve the target PRD, let $\{y_i\}, \forall i = 1, \cdots, N$, be the set of subband signals, of any input block, and be the threshold. The thresholding algorithm works as follows:

1. *Initialisation of the threshold and interval for possible thresholds:*
   (a) $_0 = \max_{\forall y_i \in y}(|y_i|/2)$.
   (b) $= _0$.
   (c) $[\ _{inf},\ _{sup}]$ *so that* $_{inf} = 0$ and $_{sup} = 2 \cdot$.
2. *Thresholding:*
   $\{y_i\}_{i=1,\cdots,N} \in y \;\Rightarrow\; y_i = 0 \quad \forall\, |y_i| <$.
3. *New threshold and interval for possible thresholds:*
   (a) *If* $PRD > PRD_{target}$: $_{sup} =$ *and* $= \left(\ _{sup} + \ _{inf}\right)/2$
   (b) *If* $PRD < PRD_{target}$: $_{inf} =$ *and* $= \left(\ _{sup} + \ _{inf}\right)/2$
4. *If* $PRD_{target} \times 0.95 \leqslant PRD \leqslant PRD_{target} \times 1.05$
   (a) *If true: the threshold is* .
   (b) *If false: go to step* 2.

Once the corresponding thresholded signal is obtained, the resulting samples are entropy–encoded as proposed in [3]. The significant coefficients are grouped and encoded with 8 bits per sample. A significance map is generated assigning '1' to the significant coefficients and '0' to the others. The map is then organised as a set of 8–bits integers. Finally, both the significant coefficients and significance map are encoded using the Huffman coder proposed in [9].

Note that the proposed method is computationally simple, enabling real–time processing of ECG signals. Also, the method does not require any prior knowledge of the ECG waveform, and can therefore be applied to any recorded signal.

3. RESULTS

The proposed method is tested utilising the MIT–BIH Arrhythmia Database. Files in the database represent two lead recordings sampled at 360 Hz with 11 bits per sample of resolution. We compare the proposed method to that in [3], which is a threshold–based ECG compression designed with the Discrete Wavelet Transform. This method has proven to be the best among other threshold–based algorithms reported in the literature. To have a direct comparison, we use the same data set as [3] for testing: the first of 2–minutes long lead extracted from records 100, 101, 102, 103, 107, 109, 111, 115, 117, 118 and 119. The 1024–baseline that was added to each lead for storage purposes was removed before processing.

The signals are processed utilising blocks of 1024 samples ($N = 1024$). To attain a fair comparison with the method

Table 1: Compression results.

Proposed method	PRD1	4.64	5.04	6.03	6.52	7.24	8.33	10
	PRD	2.67	2.90	3.46	3.74	4.15	4.79	5.76
	CR	9.13	9.88	11.36	11.90	12.60	13.53	14.69
[3]	PRD1	—	—	—	—	—	—	—
	PRD	2.64	2.88	3.46	3.73	4.15	4.80	5.76
	CR	7.05	8.28	10.89	11.62	12.46	13.49	14.74

Table 2: Comparison with other methods.

Method	*Señal*	*CR*	*PRD*[a]	*PRD1*	*PRDcc*
Proposed	117	8.58	1.1941	4.0577	0.2328
		16.46	2.5340	8.6108	0.4940
	119	17.27	5.3558	10.3394	1.2700
	232	9.25	6.3196	10.7779	0.2957
[1]	117	8	2.6	—	—
[2]	117	8	1.18	—	—
[3]	117	16.24	2.55	—	—
	119	17.43	5.1268	—	—
	232	9.04	—	—	0.2981

[a]PRD has been obtained with (1) after removing the 1024–baseline; PRD1 has been obtained with (2) and PRD_{cc} with (1) but with the corresponding baseline included.

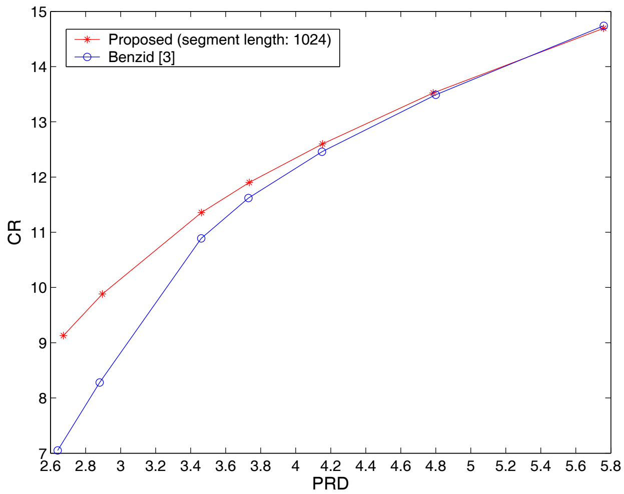

Figure 2: Performance of proposed algorithm.

in [3] the PRD_{target} values chosen are those given in Table 1 of this reference, i.e., the targets were selected to match the PDR values achieved in [3]. The results, as a function of PDR, for the two methods are given in Fig. 2. As the figure shows, the proposed method yields improved compression ratios. Best results are obtained in the range of less PRD values, corresponding to the area of high quality for the recovered signal. As can be seen in Table 1, these values correspond to PRD1 less than 9 %, i.e, the range where we were interested in enhancing. This figure also shows that the proposed method achieves a PRD very close to the target value. This can also be seen in Table 1, which lists the achieved PRD, PDR1 and CR values for each method.

Finally, the comparison of the proposed method with other approaches is given in Table 2. Distortion measurement is given in three different ways depending on whether PRD

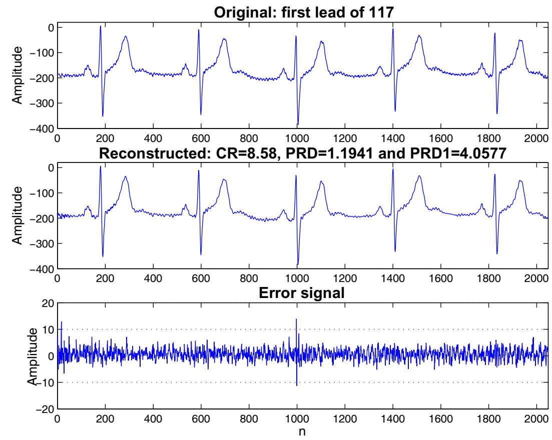

Figure 3: Compression waveforms of record 117 for $PRD = 1.1941$.

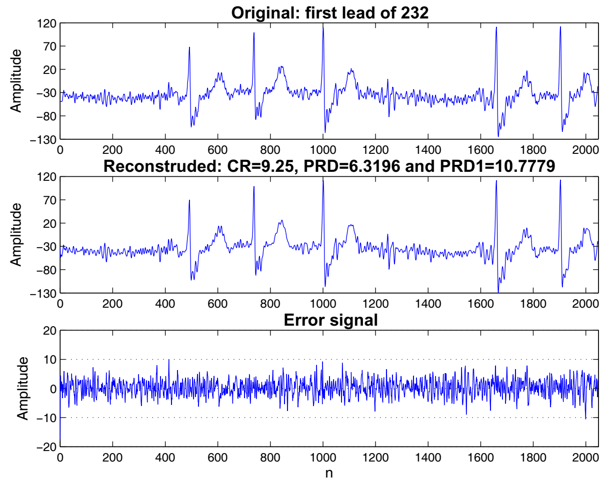

Figure 4: Compression waveforms of record 232 for $PRD = 6.3196$.

formula (1) or (2) is used as well as whether 1024–baseline is rejected or not. Note the great differences among them.

In order to have a good idea about the behaviour of the compressor, it is interesting to make the study of waveforms including the analysis of error signal. Records 117 and 232 have been chosen as examples of normal and abnormal rhythm respectively. Both Fig. 3 and Fig. 4 show, from top to bottom, the first 2048 samples of the original, the reconstructed and the error signals. Compression has been done according to the the results included in Table 2 for the corresponding 2–minute long signals. In both cases, the reconstructed signals remain close to the original ones being the error signals equally distributed along the horizontal axis.

Fig. 5 and 6 show the previous waveforms when compressing with higher PRD_{target}, i.e., demanding less quality for the reconstruction. Therefore, these graphics depict retrieved signals with more distortion. In both cases, compression has been done in such a way that the CR obtained is almost the same. Like other threshold–based compressors, the proposed one behaves as a low–pass filter, so most of the efforts for compressing are spent on smoothing the ECG. Thus

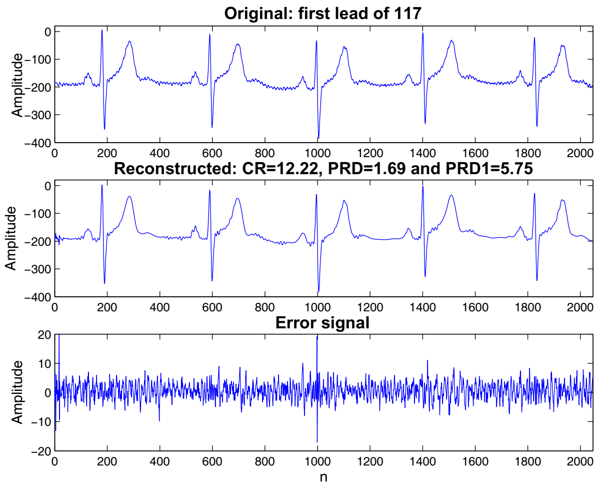

Figure 5: Compression waveforms of record 117 for $PRD = 1.69$.

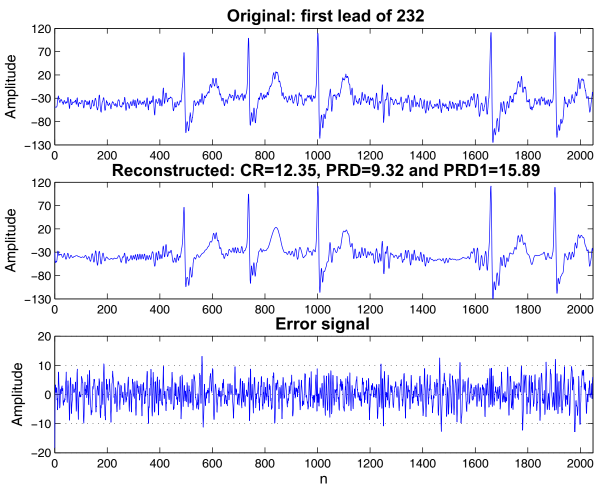

Figure 6: Compression waveforms of record 232 for $PRD = 9.32$.

for similar CRs, record 232 has worse PRD than record 117 since the first one is noisier than the second one. This means that noisy signals can be compressed with lower constraints in quality: even though the error signal increases, the retrieved one remains similar to the original since the distortion is due to the smoothing.

On the other hand, as can be appreciated in the error signal of Fig. 5, there is a high local value around $n = 1000$, which could be interpreted as the distortion between consecutive blocks of incoming signals. Fig. 7 depicts the error signal over the full range of samples. As we remarked before, error is also equally distributed along the axis appearing the greatest differences only very few times. So there is no distortion between consecutive blocks.

4. CONCLUSIONS

In this work, a cosine modulated filter bank–based compression algorithm for ECG signal is presented. The main feature of the proposed compression method is that the quality of the reconstructed signal can be ensured beforehand. Moreover, the method does not require any *a priori* signal information, and can thus be applied to any ECG. The method is also computationally simple, enabling real–time implementation. Moreover, evaluations show that it yields better compression ratios than the method reported in [3], which, to this point, is the best wavelet thresholding–based ECG compression method reported in the literature.

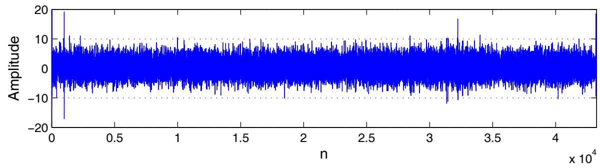

Figure 7: Whole error signal of record 117.

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References

[1] M. L. Hilton, “Wavelet and wavelet packets compression of electrocardiogram,” *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 5, pp. 394–402, May 1997.

[2] Z. Lu, D. Y. Kim, and W. A. Pearlman, “Wavelet compression of ECG signals by the set partitioning in hierarchical trees algorithm,” *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 7, pp. 849–856, Jul 2000.

[3] R. Benzid, F. Marir, A. Boussaad, M. Benyoucef, and D. Arar, “Fixed percentage of wavelet coefficients to be zeroed for ECG compression,” *Electronics Letters*, vol. 39, no. 11, pp. 830–831, May 2003.

[4] M. C. Aydin, A. E. Çetin, and H. Köymen, “ECG data compression by sub–band coding,” *Electronics Letters*, vol. 27, no. 4, 1991.

[5] A. E. Çetin, H. Köymen, and M. C. Aydin, “Multichannel ECG data compression by multirate signal processing and transform domain coding techniques,” *IEEE Transactions on Biomedical Engineering*, vol. 40, no. 5, pp. 495–499, May 1993.

[6] M. Blanco-Velasco, F. Cruz-Roldán, F. López-Ferreras, A. Bravo-Santos, and D. Martínez-Muñoz, “A low computational complexity algorithm for ECG signal compression,” *Medical Engineering and Physics*, vol. 26, no. 7, pp. 553–568, Sep 2004.

[7] Y. Zigel, A. Cohen, and A. Katz, “The Weighted Diagnostic Distortion (WDD) measure for ECG signal compression,” *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 11, pp. 1422–1430, November 2000.

[8] F. Cruz-Roldán, P. Amo-López, S. Maldonado-Bascón, and S. S. Lawson, “An efficient and simple method for designing prototype filters for cosine-modulated pseudo-QMF banks,” *IEEE Signal Processing Letters*, vol. 9, no. 1, pp. 29–31, Jan 2002.

[9] K. Skretting, “Arithmetic coding and Huffman coding in Matlab,” (online) `http//www.ux.his.no/~karlsk/proj99/`, 2004.